Improving Accuracy of Recommendation Systems with Deep Learning Models

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Abstract. Recommendation systems have been demonstrated to be an effective strategy for preventing information overload due to the ever-increasing amount of online information. It is impossible to overestimate the effectiveness of recommendation systems, considering their general employment in online applications and their ability to relieve a range of difficulties related to excessive options. For a variety of reasons, including its superior performance in computer vision as well as natural language processing (NLP), deep learning (DL) has gained considerable scholarly interest in recent years but also to its appealing potential to start from scratch and learn how to express features. Deep learning has recently proved its use in information retrieval along with recommendation system research, demonstrating its pervasiveness. The area of recommendation systems that combines deep learning is booming. Deep learning-based recommendation systems are the subject of much current research, which is summarized in this article. A comprehensive analysis of the current status of deep learning-based recommendation models is presented in this research paper. Last but not the least, it focuses on current developments and gives new insights on this cutting-edge new industry.

Keywords: Recommendation systems, deep learning, natural language processing, recommender systems, Convolutional Neural Network, content-based filtering system, collaborative recommendation system, hybrid recommendation system**.**

1 Introduction

Recommendation systems offer a comprehensible barrier against customer over-selection. Because of the rising growth of publicly accessible data, internet users are frequently given an oversupply of items, movies, and restaurants to pick from. As a consequence, increasing the user experience necessitates incorporating personalization tactics. These systems are widespread throughout several online domains, including e-commerce along with social media websites Zhang et al. [1]. For commercial and decision-making purposes, they play a key and important role in many information access systems. If someone is using a Point-of-Interest (POI) recommender to build a list of recommendations, they often see a combination of user preferences and item characteristics, as well as historical interactions between users and products. Content-based recommendation systems, collaborative filtering-based recommendation systems, and hybrid recommendation systems are all subcategories of recommendation models Mansur, Patel and Patel [2]. Many disciplines, including computer vision, voice recognition, and the recommendations systems mentioned above have successfully used DL in the previous few decades. Academics and industry alike are rushing to discover new applications for deep learning since it can tackle a broad variety of complicated challenges with cutting-edge outcomes Liu et al. [3]. Recently, deep learning has dramatically altered the design of recommendation systems, introducing new possibilities to increase their efficacy. People's attention has been drawn to profound learning-based improvements in recommendation systems because they go beyond the limitations of previous models and provide high-quality recommendation output. For example, DL may be able to capture complicated interactions between users and items in a non-trivial and non-linear manner, allowing for the creation of higher-level data representations of these interactions. It also catches the subtle connections that arise when different data sources, such as contextual as well as visual data, are used together.

1.1 Background of the Study

Recommendation systems are frequently employed by many online and mobile apps to improve user experience and increase sales and services Rong et al. [4]. For instance, recommendations contributed to 80 percent of Netflix movie views Smith and Linden [5], and home page suggestions accounted for 60 percent of YouTube video views Kirdemir et al. [6]. A growing number of firms have been adopting deep learning to boost the quality of their recommendation systems in recent years. Almabdy and Elrefaei [7] established a deep neural network (DNN)-based YouTube video recommendation system. Cheng et al. [8] built a comprehensive and deep model for a Google Play app recommendation system. De Souza Pereira Moreira [9] demonstrated a news recommendation system based on Yahoo News RNN. During online testing, all of these models were much better than the usual models. As a result, deep learning has resulted in a dramatic transition in industrial recommender applications-Deep learning-based recommendation algorithms have seen a large surge in research papers published in recent years, offering persuasive evidence that the technique has vast potential for application in recommendation system research. Recommender System (RecSys), the top international conference on recommendation systems, has included a monthly deep learning session since 2016 Fessahaye et al. [10]. The goal of this international conference was to promote research into deep learning-based recommendation systems and to stimulate their implementation. For future researchers and practitioners to fully grasp the advantages and drawbacks of deep learning models, a thorough examination and overview is required.

1.2 Current Challenges

There are some limitations associated with the use of recommendation systems, some of which are as under:

- **Cold Start problem**

The cold start issue commonly happens when a new user joins the site or introduces a new item to the system. Second, who can this new item be recommended to? No one has given it a rating; therefore, no one knows whether it is good or poor.

- **Sparsity Problem**

The Sparsity Problem occurs when a customer is presented with many things to choose from, movies to view, or music to listen to, all at the same time. In this case, sparsity was caused by the user's failure to rank these things. When it comes to making suggestions to other people, recommendation systems depend on user evaluations of specific persons.

- **Scalability**

The ability of a system to work successfully with high performance despite growing in information is measured by scalability.

- **Privacy concerns**

Given multiple high-profile examples of consumer data leaks in recent years, many customers are cautious about passing out personal information. On the other hand, the recommendation engine cannot work successfully without this client data. As a result, establishing trust between the company and its customers is critical.

- **Quality**

Users may lose trust in the site if the recommendation engine does not provide good recommendations.

1.3 Problem Statement

It is common for users to feel overwhelmed or perplexed by the fast expansion in the number and diversity of Internet-accessible information resources, as well as the quick development of new e-business services such as buying things, product comparison, auctions, etc. In turn, people make bad judgments as a consequence. It isn't easy to gather accurate automatic information from varied forms of material (e.g., photographs, video, audio, and text), which causes a significant challenge in the recommendation system. As a result, the quality of recommendations is significantly reduced. When it comes to content-based recommendation systems, overspecialization is one of the most common issues they have to deal with.

An approach to coping with the problems of restricted content analysis and overspecialization in recommendation systems is shown by this study effort in this article. When a user comes across a product that they are unfamiliar with or for which they do not know the precise name or description, this system will aid them in identifying the object. This suggested recommendation system collects and analyses consumer information in real-time, resulting in customized suggestions for the consumers based on their preferences. They depend on implicit and explicit data, such as browsing history and purchases, and user ratings to function correctly.

Using machine learning, optimize the ranking system of the search results after each search in order to provide the customer with more precise products that are of interest to the customer, resulting in a rise in sales and customer registration. The following objectives may assist in achieving this goal:

- To review previous research on machine learning models built for product recommendation in the case of limited content.
- To develop recommendation models using different deep learning algorithms to aid in prediction in an online recommendation system.
- To analyze and compare the accuracy of Convolution Neural Networks (CNNs),Long Short-Term Memory (LSTM) AND Recurrent Neural Networks (RNNs).

• To refine and update the best performing Hybrid model obtained as the outcome of analysis.

2 Recommendation Systems

User-friendly recommendations are provided by recommendation systems (RSs), which are software tools and methods that propose products that a user may find helpful. What should be bought, what music should be listened to, and what online news should be read are examples of the kind of decisions the users should make based on their recommendations.

2.1 Overview of Recommendation Systems

Users' item selections are analyzed by recommendation systems, which then make ideas for other goods they might enjoy He, Parra and Verbert [11] .There are three basic recommendation models: content-based filtering recommendation system, collaborative filtering recommendation system, and hybrid recommendation system Hwang and Park [11]. As a consequence of prior interactions between the user and an item, collaborative filtering provides suggestions, including browsing history. Most of the content-based recommendation is made using comparisons between items and other user information .A variety of extra data, including essays, photos, and videos, Hwang and Park might be evaluated. When a recommendation system adopts a hybrid model, it contains more than one form of recommendation algorithm Patel and Dharwa [13]. Recommendation systems have aided in the improvement of quality and decision-making. Recommendation systems generate a list of recommendations for a user in one of four methods. They are Content, Collaborative, Demographic, Hybrid filtering based methods. The following is a real-time interaction with a recommended system:

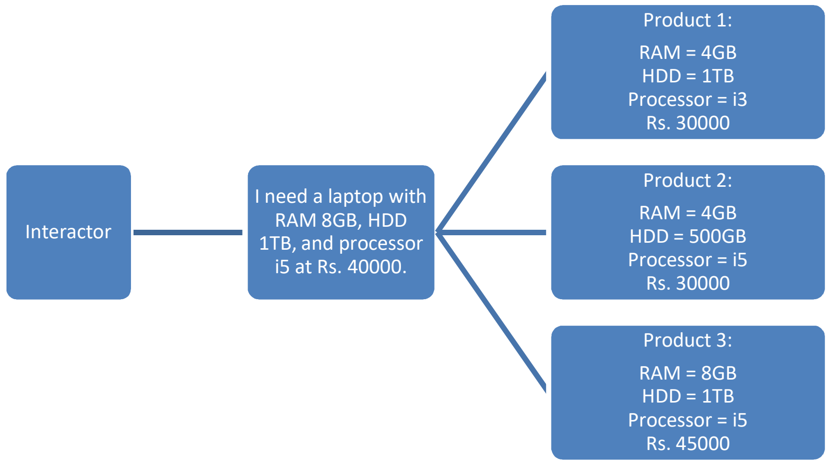

Figure 1: Example of a real-time interaction with a recommended system

3 MLP-Based Models for Recommendation Systems

Human visual attention supports the process of attentiveness. To receive or understand visual inputs, humans, for instance, need merely concentrate on specified areas. Non-informative properties of raw inputs may be filtered out by attention processes, decreasing the detrimental repercussions of noisy data. Computer vision, natural language processing, and voice recognition have all witnessed a boom in interest in this technology in the previous few years. It is a simple yet powerful approach (Kunze et al.[14]. Neural networks may be utilized not simply with Convolutional Neural Networks(CNNs), Multi-Layer Perceptron (MLP), Recurrent Neural Networks (RNNs), etc., but also for specific tasks Garnot et al.[15].

RNNs may manage a noisy and long-running input by integrating an attention mechanism Hsiao and Chen[16]. Although Long Short-Term Memory (LSTM) may potentially lessen the prolonged memory issue, it is still difficult to cope with long-distance interdependence. The attention strategy provides a better response and helps the network remember inputs more effectively. Attention-based CNNs can extract the most helpful input features Basiri et al. [17]. Include an attention function in the recommendation system to minimize extraneous data and pick the most representative objects while still keeping a high degree of understandability (Alhamdani, Abdullah, and Sattar [18]. As a consequence of its broad application, neural attention mechanisms may be regarded a stand-alone deep neural approach.

Keerthika and Saravanan [19] provide a novel strategy for variety recommending that takes into account user demographics as well as item seasonality in a single approach. Seasonal products available throughout the user's chosen season would considerably increase their appreciation of the product. Customer satisfaction is reduced as a result of the cold start issue. When it comes to product coverage and uncertainty, diversity's effectiveness with a seasonal strategy has been shown in various sectors.

According to Arora, Bali and Singh [20], recommendation systems may anticipate whether or not a user would prefer a specific item based on the user's profile and previous purchases. According to the findings of this study, seasonal goods should be offered to consumers who have a high degree of seasonality in their preferred season.

Concerning each of these categories, Shah, Gaudani, and Balani [21] present an overview of the several ways and obstacles faced in each of them. There are three basic strategies for developing a customized recommendation system including content-based filtering recommendation system, collaborative filtering recommendation system, and a hybrid approach to recommending material. The authors created a recommendation system to assist consumers in finding more relevant items or services from the firm's point of view while simultaneously increasing productivity and revenues for the company.

Roy, Choudhary, and Jayapradha [22] stress the need to develop an efficient product recommendation system that uses Linear Regression. The computer calculates the optimal cost value from the linear regression approach and displays it on a screen using machine learning. Product suggestions will study the currently available goods to find the most often bought items that the consumer appreciates and wishes to acquire.

Ahmed et al. [23] developed a recommendation system for the pharmaceutical industry using a comprehensive and deep learning model for large-scale industrial recommendation tasks that is coupled to the local environment. It does away with the necessity for deep learning altogether in favor of a rapid, local network, leading to a substantial reduction in the total execution time of the algorithm. The selection of broad and deep features is critical in developing wide and deep learning. That is, the system must distinguish between characteristics that can be recalled and those that are more general. In addition, users have to construct the cross-product transformation manually. The usefulness of this model will be significantly influenced by the stages that came before it. Following a deep factorization technique, as previously indicated, the amount of effort spent on feature engineering might be reduced significantly.

Rendle et al. [24] investigated the usage of MLP for YouTube recommendations in their research. The two components of this approach are the production of candidates and the assessment of candidates. Hundreds of video samples are transmitted to the candidate generation network to narrow the field of candidates. An initial top-n list of candidates based on the scores of their nearest neighbors is provided by the ranking network It is important to consider the engineering of features like transformation, normalization, and cross-validation, as well as the scalability of recommendation models in an industrial context.

Naumov et al. [25] proposed an MLP-based model for recommending cosmetics. Expert rules and labelled occurrences may be simulated using two identical MLP models. The output difference between these two networks is decreased, which concurrently changes the parameters of both networks. That expert information may have a significant influence on the recommendation model's learning process within an MLP framework is illustrated in this case study. It is accurate even though obtaining the essential competency involves extensive human involvement.

According to Wang et al. [26], who researched the influence of visual elements on POI recommendation, an improved POI recommendation system that combines visual information was created (VPOI, i.e., Visual Point-of-Interest). VPOI exploits CNNs to extract visual characteristics. Based on Probabilistic Matrix Factorization (PMF), the recommendation model is constructed by studying the correlations between visual material and a user's underlying psychological state.

Cheng et al. [27] evaluated the efficacy of visual information in restaurant suggestions, such as images of cuisine and restaurant décor. The performance of Matrix Factorization (MF), and Bayesian Personalized Ranking Matrix Factorization (BPRMF) may be assessed using the visual qualities and text representations retrieved by CNN. The data reveal that visual information enhances performance modestly but not drastically.

Incorporating visual cues (acquired through CNNs) with matrix factorization, He and McAuley [28] constructed a Visual Bayesian Personalized Ranking (VBPR) system. A linked matrix and tensor factorization approach for aesthetic-based clothing selection has been developed by Kang et al. [26] and Yu et al. [29] to analyze the visual features of apparel and aesthetic features that users consider when choosing to clothe. This approach is used to increase VBPR by analyzing users' fashion awareness as well as the growth of visual characteristics that users consider when choosing to clothe.

Zheng et al. [30] introduced a CNN-based technique for configurable tag recommendation. Visual attributes from picture patches are retrieved using convolutional and max-pooling layers. User data is incorporated in the recommendation to produce customized recommendations. To develop this network, it was chosen to apply the Bayesian Personalized Ranking (BPR) objective of expanding the distance between relevant and irrelevant tags. Using deep learning and CNNs, Audebert, Le Saux, and Lefèvre [31] built a picture recommendation model. CNNs and MLPs are used in this network to learn visual representations and user preferences. It performs a side-by-by comparison of the user's preferred and least loved images. A tag recommendation system that considers context was suggested by Haruna et al. [32]. CNNs learn the image's attributes. The authors processed the context representations using a two-layered feedforward neural network with complete connectivity. A SoftMax function is used to forecast the likelihood of candidate tags by feeding the outputs of two neural networks together.

Encoding text sequences using latent component models and Gated Recurrent Units (GRUs) was suggested by Bansal et al.[33]. Warm-start and cold-start difficulties are both solved by this hybrid design. As mentioned above, a multi-task regularizer was also applied to avoid overfitting and relieve sparse training data. Predicting ratings is critical, with item meta-data predictions being a close second (e.g., tags, genres). Employing a latent component model, Perera [34] recommended employing GRUs to discover more expressive aggregations of user browsing history. The results demonstrate a considerable improvement over the usual word-based technique. Daily, over ten million unique users are managed by the system.

For the recommendation of quotations, Alhamdani et al. [35] developed a deep hybrid model using RNNs and CNNs. Quote recommendation is the process of generating a prioritized list of relevant quotations from given query texts or chats (each debate comprises a series of tweets). What it does is extract relevant semantics from tweets using a convolutional neural network (CNN). Then, it converts the meaning of the tweet into its distribution vector. In order to identify the relevancy of target quotations in particular Twitter chats, the distributional vectors are analyzed using LSTM. For hashtag recommendation, Zhang et al. proposed a CNN/RNN hybrid model (2019). CNNs were used to extract textual data from a tweet that included graphics, and LSTM was used to learn textual features from the tweet. In the meanwhile, researchers came up with a way to replicate correlation effects and balance the contributions of words and images.

Ebesu and Fang [36] created a neural citation network that includes CNNs and RNNs for citation recommendation in an encoder-decoder configuration using an encoder-decoder architecture. CNNs encode long-term associations based on the context of the citation. Decoding the title of the referenced article is accomplished by using RNNs, which operate as decoders, learning the probability that a specific word will occur in the title from the title's preceding words and the CNN representations. Huang and Wang [37] suggested an integrated CNN and RNN system for personalized keyframe recommendation concerning keyframe recommendation. CNNs learn feature representations from keyframe visual representations, and RNNs analyze textual features of keyframes.

4 CNNfor Recommendation Systems

To understand why deep learning approaches are being used in recommendation systems, it is vital to know the nuances of recent achievements. In a short amount of time, the validity of various deep recommendation systems has been shown. This industry is, indeed, a hub of the invention. At this stage, it's simple to dispute the need for so many diverse designs, as well as the use of neural networks in the subject area under consideration. It is also vital to explain why and under what circumstances a design approach makes sense. This challenge addresses subjects such as tasks, domains, and recommender scenarios. End-to-end differentiability and input-specific inductive biases are two of neural networks' most desirable qualities. Therefore, deep neural networks should be favorable if the model can use an inherent structure. CNNs and RNNs, for instance, have employed the inherent structure in vision (and/or human language) for quite some time. Recurrent/convolutional models benefit considerably from the inductive biases generated by session or click-log data because of the sequential structure of the data Zhang and Liu [38].

It is also feasible to train a deep neural network from scratch by combining several neural building blocks into a single (significant) differentiable function. The capacity to make suggestions based on the information itself is the primary advantage of this technique. Due to the prevalence of multi-modal data on the Internet, this is inevitable whether portraying people or goods. Using CNNs and RNNs as neural building blocks is crucial when dealing with textual and visual data (social posts, product images). The recommendation system cannot use end-to-end joint representation learning since a common alternative that recognizes modality-specific characteristics becomes much less attractive. Recommendation systems are intricately tied to advances in vision and language, as well as other fields of research. Newer deep learning-based systems may consume all textual input end-to-end rather than needing expensive preprocessing (such as crucial word extraction and topic modeling, for example) (Roy et al. [39]. Without these new improvements, it would be challenging to express graphics and interactions in a unified framework Liu et al. [38]. It becomes acceptable to utilize deep neural networks when dealing with a challenge like a matrix completion or a collaborative ranking problem requiring many training instances.

To estimate the interaction function, Kang and McAuley [40] employed an MLP and found it performed better than more standard approaches like MF. The scientists found that standard machine learning models including MF, BPR, and Collaborative Metric Learning (CML) performed well when trained only on interactions using momentum-based gradient descent Vinh et al. [41]. However, since they include more recent deep learning advancements like Adam and Dropout, these models might be referred to as "neural architectures" Garbin, Zhu and Marques [42]. A framework like as TensorFlow or PyTorch may classify traditional recommender systems like matrix factorization and factorization machines as neural/differentiable structures Jawad and Islam [43]. There is no reason why deep learning-based technology should not be used to create recommendation systems in today's academic and business sectors.

Table 1. Comparison Tables.

CNN Architecture	Pretrained Network	Fixed Feature Extraction Method	Fine-Tuning Method
Input	Pretrained convolutional base	Pretrained convolutional base	Fine-tuned convolutional base
Output	Pretrained fully connected layers	New classifier	New fully connected layers

The different CNN designs and implementations are compared and compared in Table 1. Convolution, pooling, and fully connected (FC) layers are stacked using three distinct algorithms. Loss functions are computed on a training dataset to evaluate the model's performance with different kernels and weights. Following that, the gradient descent optimization algorithm ReLU and backpropagation are employed to change learnable parameters based on the loss value.

5 Conclusion

This review article presented a detailed assessment of the most noteworthy work on deep learning-based recommendation systems. Several significant research prototypes were provided as well as a categorization approach for current publications. In addition, the restrictions of employing deep learning systems for recommendation tasks were examined. In addition, it addresses some of the most crucial unresolved challenges and the most expected future advances. In the last couple of decades, deep learning and recommendation systems have become prominent study disciplines. Each year, there are many unique approaches and models under development. This study aimed to present readers with a complete analysis of the most critical components of this discipline along with shedding light on the most significant advances.

References

1. Fessahaye, F., Perez, L., Zhan, T., Zhang, R., Fossier, C., Markarian, R., Chiu, C., Zhan, J., Gewali, L. and Oh, P., 2019, January. T-recsys: A novel music recommendation system using deep learning. In 2019 IEEE international conference on consumer electronics (ICCE) (pp. 1-6). IEEE.
2. Mansur, F., Patel, V. and Patel, M., 2017, March. A review on recommendation systems. In 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS) (pp. 1-6). IEEE.26
3. Liu, B., Ding, M., Shaham, S., Rahayu, W., Farokhi, F. and Lin, Z., 2021. When machine learning meets privacy: A survey and outlook. ACM Computing Surveys (CSUR), 54(2), pp.1-36

4. Rong, H., Wang, Y., Zhou, F., Zhai, J., Wu, H., Lan, R., Li, F., Zhang, H., Yang, Y., Guo, Z. and Wang, D., 2020, July. Distributed equivalent substitution training for large-scale recommendation systems. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 911-920).
5. Smith, B. and Linden, G., 2017. Two decades of recommendation systems at Amazon. com. Ieee internet computing, 21(3), pp.12-18.
6. Kirdemir, B., Kready, J., Mead, E., Hussain, M.N. and Agarwal, N., 2021, April. Examining video recommendation bias on YouTube. In International Workshop on Algorithmic Bias in Search and Recommendation (pp. 106-116). Springer, Cham.
7. Almabdy, S. and Elrefaei, L., 2019. Deep convolutional neural network-based approaches for face recognition. Applied Sciences, 9(20), p.4397.
8. Cheng, H.T., Koc, L., Harmsen, J., Shaked, T., Chandra, T., Aradhye, H., Anderson, G., Corrado, G., Chai, W., Ispir, M. and Anil, R., 2016, September. Wide & deep learning for recommendation systems. In Proceedings of the 1st workshop on deep learning for recommendation systems (pp. 7-10).
9. De Souza Pereira Moreira, G., 2018, September. CHAMELEON: a deep learning meta-architecture for news recommendation systems. In Proceedings of the 12th ACM Conference on Recommendation systems (pp. 578-583).12
10. Fessahaye, F., Perez, L., Zhan, T., Zhang, R., Fossier, C., Markarian, R., Chiu, C., Zhan, J., Gewali, L. and Oh, P., 2019, January. T-recsys: A novel music recommendation system using deep learning. In 2019 IEEE international conference on consumer electronics (ICCE) (pp. 1-6). IEEE.
11. He, C., Parra, D. and Verbert, K., 2016. Interactive recommender systems: A survey of the state of the art and future research challenges and opportunities. Expert Systems with Applications, 56, pp.9-27.
12. Hwang, S. and Park, E., 2021. Movie Recommendation Systems Using Actor-Based Matrix Computations in South Korea. IEEE Transactions on Computational Social Systems.
13. Patel, A.A. and Dharwa, J.N., 2016, March. Fuzzy based hybrid mobile recommendation-system. In Proceedings of the Second International Conference on Information and Communication Technology for Competitive Strategies (pp. 1-6).
14. Kunze, J., Kirsch, L., Kurenkov, I., Krug, A., Johannsmeier, J. and Stober, S., 2017. Transfer learning for speech recognition on a budget. arXiv preprint arXiv:1706.00290
15. Garnot, V.S.F., Landrieu, L., Giordano, S. and Chehata, N., 2020. Satellite image time series classification with pixel-set encoders and temporal self-attention. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 12325-12334).
16. Hsiao, P.W. and Chen, C.P., 2018, April. Effective attention mechanism in dynamic models for speech emotion recognition. In 2018 IEEE international conference on acoustics, speech and signal processing (ICASSP) (pp. 2526-2530). IEEE.
17. Basiri, M.E., Nemati, S., Abdar, M., Cambria, E. and Acharya, U.R., 2021. ABCDM: An attention-based bidirectional CNN-RNN deep model for sentiment analysis. Future Generation Computer Systems, 115, pp.279-294.
18. Alhamdani, R., Abdullah, M. and Sattar, I., 2018. Recommendation system for global terrorist database based on deep learning. International Journal of Machine Learning and Computing, 8(6), pp.571-576
19. Keerthika, K. and Saravanan, T., 2020, December. Enhanced Product Recommendations based on Seasonality and Demography in Ecommerce. In 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN) (pp. 721-723). IEEE.

20. Arora, K., Bali, V. and Singh, S., 2017. RECOMMENDATION SYSTEMS: A REVIEW REPORT. International Journal of Advanced Research in Computer Science, 8(7)
21. Shah, L., Gaudani, H. and Balani, P., 2016. Survey on recommendation system. International Journal of Computer Applications, 137(7), pp.43-49.
22. Roy, K., Choudhary, A. and Jayapradha, J., 2017. Product recommendations using data mining and machine learning algorithms. ARPN Journal of Engineering and Applied Sciences, 12(19).
23. Ahmed, A., Saleem, K., Khalid, O. and Rashid, U., 2021. On deep neural network for trust aware cross domain recommendations in E-commerce. Expert Systems with Applications, 174, p.114757.
24. Rendle, S., Krichene, W., Zhang, L. and Anderson, J., 2020, September. Neural collaborative filtering vs. matrix factorization revisited. In Fourteenth ACM conference on recommendation systems (pp. 240-248).
25. Naumov, M., Mudigere, D., Shi, H.J.M., Huang, J., Sundaraman, N., Park, J., Wang, X., Gupta, U., Wu, C.J., Azzolini, A.G. and Dzhulgakov, D., 2019. Deep learning recommendation model for personalization and recommendation systems. arXiv preprint arXiv:1906.00091.
26. Kang, W.C., Fang, C., Wang, Z. and McAuley, J., 2017, November. Visually-aware fashion recommendation and design with generative image models. In 2017 IEEE international conference on data mining (ICDM) (pp. 207-216). IEEE
27. Cheng, Z., Chang, X., Zhu, L., Kanjirathinkal, R.C. and Kankanhalli, M., 2019. MMALFM: Explainable recommendation by leveraging reviews and images. ACM Transactions on Information Systems (TOIS), 37(2), pp.1-28.
28. He, R. and McAuley, J., 2016, February. VBPR: visual bayesian personalized ranking from implicit feedback. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 30, No. 1).
29. Yu, W., Zhang, H., He, X., Chen, X., Xiong, L. and Qin, Z., 2018, April. Aesthetic-based clothing recommendation. In Proceedings of the 2018 world wide web conference (pp. 649-658).
30. Zheng, L., Tianlong, Z., Huijian, H. and Caiming, Z., 2020. Personalized tag recommendation based on convolution feature and weighted random walk. International Journal of Computational Intelligence Systems, 13(1), pp.24-35
31. Haruna, N., Le Saux, B. and Lefèvre, S., 2019. Deep learning for classification of hyperspectral data: A comparative review. IEEE geoscience and remote sensing magazine, 7(2), pp.159-173.
32. Haruna, K., Akmar Ismail, M., Suhendroyono, S., Damiasih, D., Pierewan, A.C., Chiroma, H. and Herawan, T., 2017. Context-aware recommendation system: A review of recent developmental process and future research direction. Applied Sciences, 7(12), p.1211.
33. Bansal, T., Belanger, D. and McCallum, A., 2016, September. Ask the gru: Multi-task learning for deep text recommendations. In proceedings of the 10th ACM Conference on Recommendation systems (pp. 107-114).
34. Perera, M.D.D., 2021. Towards Comprehensive User Preference Learning: Modeling User Preference Dynamics Across Social Networks for Recommendations (Doctoral dissertation, National University of Singapore (Singapore)).
35. Alhamdani, R., Abdullah, M. and Sattar, I., 2018. Recommendation system for global terrorist database based on deep learning. International Journal of Machine Learning and Computing, 8(6), pp.571-576.

36. Ebesu, T. and Fang, Y., 2017, August. Neural citation network for context-aware citation recommendation. In Proceedings of the 40th international ACM SIGIR conference on research and development in information retrieval (pp. 1093-1096).
37. Huang, C. and Wang, H., 2019. A novel key-frames selection framework for comprehensive video summarization. IEEE Transactions on Circuits and Systems for Video Technology, 30(2), pp.577-589.
38. Zhang, Y. and Liu, X., 2021. Learning attention embeddings based on memory networks for neural collaborative recommendation. Expert Systems with Applications, 183, p.115439.
39. Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T.H. and Faubert, J., 2019. Deep learning-based electroencephalography analysis: a systematic review. Journal of neural engineering, 16(5), p.051001.
40. Kang, W.C. and McAuley, J., 2018, November. Self-attentive sequential recommendation. In 2018 IEEE International Conference on Data Mining (ICDM) (pp. 197-206). IEEE.
41. Vinh, T.D.Q., Tay, Y., Zhang, S., Cong, G. and Li, X.L., 2018. Hyperbolic recommendation systems. arXiv preprint arXiv:1809.01703.
42. Garbin, C., Zhu, X. and Marques, O., 2020. Dropout vs. batch normalization: an empirical study of their impact to deep learning. Multimedia Tools and Applications, 79(19), pp.12777-12815.
43. Jawad, M.A. and Islam, M.S., 2019. Improving Deep Learning Based Recommendation systems Using Dimensionality Reduction Methodologies (Doctoral dissertation, Deparment of Computer Science and Engineering, Islamic University of Technology, Gazipur, Bangladesh).